## **ML**part

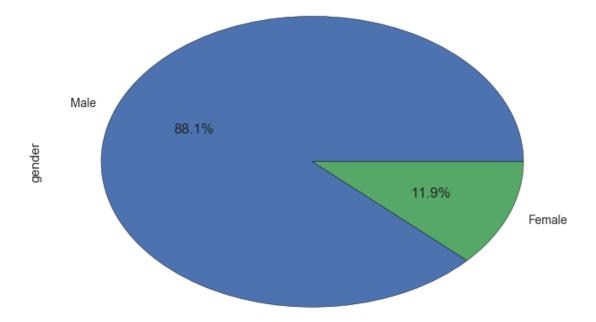
June 22, 2017

```
In [117]: %matplotlib inline
          import pandas as pd
          import matplotlib.pyplot as plt
          import matplotlib.pyplot as plt
          import seaborn
          seaborn.set(style='ticks')
          from IPython.display import Audio
          import numpy as np
          import scipy
          import mir_eval
          import librosa
          d = pd.read_csv("/Users/reyno392/Desktop/Programming/bigdataproject/output-final.csv")
          d.describe()
Out [117]:
                        mfcss0
                                       mfcss1
                                                      mfcss2
                                                                     mfcss3
                                                                                   mfcss4
          count
                 15878.000000
                                15878.000000
                                               15878.000000
                                                              15878.000000
                                                                             15878.000000
          mean
                   -423.909381
                                   159.290538
                                                 -24.893228
                                                                 15.019428
                                                                                33.746356
          std
                     94.639789
                                    29.435250
                                                  21.778312
                                                                 11.841057
                                                                                11.764870
                   -931.677719
                                    39.898847
                                                -106.694800
                                                                 -33.921526
                                                                               -29.246400
          min
          25%
                   -476.017744
                                   141.989375
                                                 -39.712573
                                                                  7.045423
                                                                                26.768538
          50%
                   -415.611308
                                                 -23.979239
                                   161.921309
                                                                 15.028690
                                                                                34.455215
          75%
                   -361.143435
                                   179.695510
                                                   -9.860378
                                                                 23.253927
                                                                                41.616460
          max
                    -92.378454
                                   258.706208
                                                  63.630408
                                                                 64.957047
                                                                                76.831597
                        mfcss5
                                       mfcss6
                                                      mfcss7
                                                                     mfcss8
                                                                                   mfcss9
                 15878.000000
                                15878.000000
                                               15878.000000
                                                              15878.000000
                                                                             15878.000000
          count
                                                   10.578178
                    -15.152955
                                     1.543789
                                                                 -11.355057
                                                                                 2.482382
          mean
          std
                     10.258179
                                                                   7.394772
                                    11.253760
                                                    8.561556
                                                                                 8.888972
                                   -43.376065
                    -60.941695
                                                  -32.931751
                                                                 -47.183815
                                                                               -29.021087
          min
          25%
                    -22.097443
                                    -6.016731
                                                    5.768405
                                                                -16.221324
                                                                                -3.295486
          50%
                    -15.092507
                                     1.132838
                                                  11.312888
                                                                 -11.326262
                                                                                 1.848496
          75%
                     -8.246649
                                    10.071626
                                                   16.437185
                                                                 -6.405290
                                                                                 9.174909
```

```
22.143577
                                    32.995945
                                                   40.878149
                                                                  13.489550
                                                                                 32.437802
          max
                                    contrast3
                                                   contrast4
                                                                  contrast5
                                                                                 contrast6
                                                15878.000000
                                                               15878.000000
                                 15878.000000
                                                                              15878.000000
          count
          mean
                                    15.594197
                                                   17.163963
                                                                  61.852865
                                                                                 14.330051
          std
                                     1.400902
                                                    1.495602
                                                                   4.411277
                                                                                   1.967879
                       . . .
          min
                                    11.467180
                                                   12.467453
                                                                  20.932720
                                                                                   4.766859
                       . . .
          25%
                                    14.667270
                                                   16.149527
                                                                  59.075275
                                                                                 13.317150
                       . . .
          50%
                                    15.400136
                                                   16.944605
                                                                  62.039100
                                                                                 14.213044
          75%
                                    16.250967
                                                   17.948888
                                                                  64.839505
                                                                                 15.451015
                                    27.526058
                                                   29.728328
                                                                  74.808438
                                                                                 34.170896
          max
                      tonnetz0
                                     tonnetz1
                                                    tonnetz2
                                                                   tonnetz3
                                                                                   tonnetz4
          count
                  15878.000000
                                 15878.000000
                                                15878.000000
                                                               15878.000000
                                                                              15878.000000
          mean
                     -0.007840
                                     0.009440
                                                    0.019431
                                                                   0.003478
                                                                                  0.000854
                      0.013069
                                                    0.067605
          std
                                     0.018001
                                                                   0.067527
                                                                                  0.014739
                     -0.081372
                                    -0.055369
                                                   -0.288997
                                                                  -0.378189
                                                                                 -0.080152
          min
          25%
                                                                  -0.025159
                                                                                 -0.004840
                     -0.013722
                                    -0.001541
                                                   -0.017952
          50%
                     -0.005926
                                     0.008093
                                                    0.006747
                                                                   0.004878
                                                                                   0.001855
          75%
                     -0.000085
                                     0.019736
                                                    0.042374
                                                                   0.032940
                                                                                   0.007944
          max
                      0.048793
                                     0.157006
                                                    0.395262
                                                                   0.394929
                                                                                   0.084532
                      tonnetz5
                  15878.000000
          count
                     -0.003816
          mean
          std
                      0.019407
          min
                     -0.100362
          25%
                     -0.011295
          50%
                     -0.000704
          75%
                      0.006958
                      0.083421
          max
          [8 rows x 193 columns]
In [103]: d.isnull().values.any()
Out[103]: False
In [104]: d.gender.value_counts().plot(kind='pie', autopct='%1.1f%%')
```

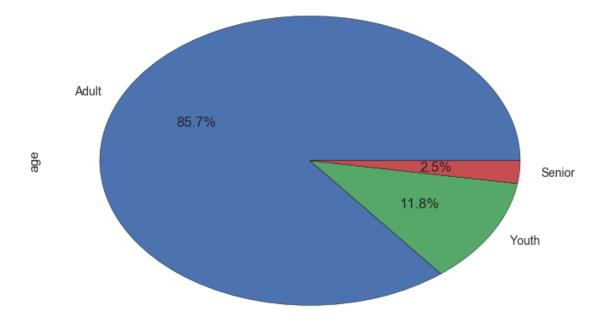
Out[104]: <matplotlib.axes.\_subplots.AxesSubplot at 0x10c7af5c0>

In []:



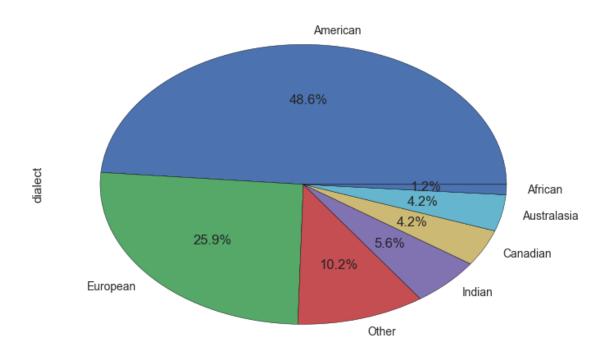
In [105]: d.age.value\_counts().plot(kind="pie", autopct='%1.1f%%')

Out[105]: <matplotlib.axes.\_subplots.AxesSubplot at 0x10c7a5278>

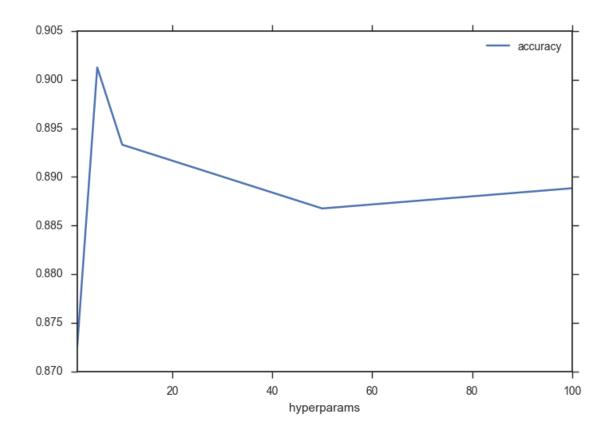


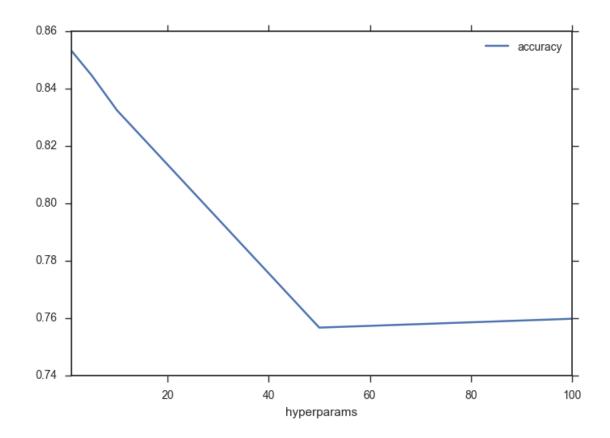
In [106]: d.dialect.value\_counts().plot(kind="pie", autopct='%1.1f%%')

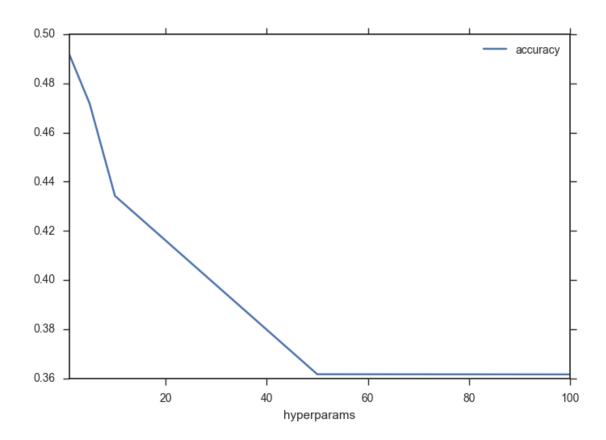
Out[106]: <matplotlib.axes.\_subplots.AxesSubplot at 0x10c7bd4e0>



```
In [107]: from sklearn.model_selection import train_test_split
          from sklearn import tree
          from sklearn.metrics import accuracy_score
          from sklearn.model_selection import cross_val_score
In [108]: d.keys()
Out[108]: Index(['Directory', 'mfcss0', 'mfcss1', 'mfcss2', 'mfcss3', 'mfcss4', 'mfcss5',
                 'mfcss6', 'mfcss7', 'mfcss8',
                 'contrast6', 'tonnetz0', 'tonnetz1', 'tonnetz2', 'tonnetz3', 'tonnetz4',
                 'tonnetz5', 'gender', 'age', 'dialect'],
                dtype='object', length=197)
In [109]: del d["Directory"]
          Y_gender = d["gender"]
          Y_age = d["age"]
          Y_dialect = d["dialect"]
          del d["gender"]
          del d["age"]
          del d["dialect"]
          X = d
In [110]: hyperparams = [1, 5, 10, 50, 100]
          accuracy = []
          for params in hyperparams:
              clf = tree.DecisionTreeClassifier(max_depth=params)
              scores = cross_val_score(clf, X, Y_gender, cv=5)
              accuracy.append(scores.mean())
          d = pd.DataFrame({"hyperparams": hyperparams, "accuracy": accuracy})
          d.plot(x="hyperparams", y="accuracy")
Out[110]: <matplotlib.axes._subplots.AxesSubplot at 0x10c8616d8>
```

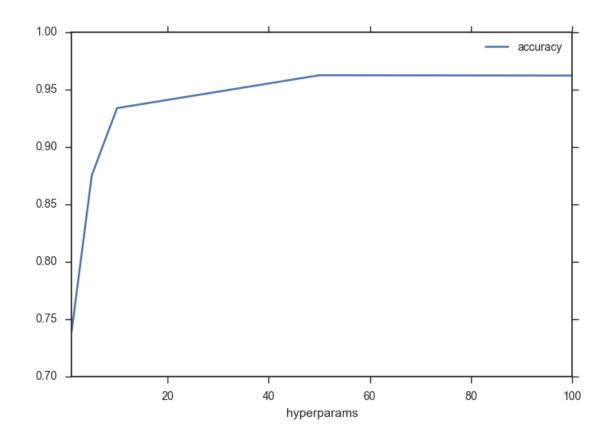






```
In [127]: y, sr = librosa.load("/Users/reyno392/Desktop/Programming/bigdataproject/data/allison-
          spectrogram = np.abs(librosa.stft(y))
          melspec = librosa.feature.melspectrogram(y=y, sr=sr)
          stft = np.abs(librosa.stft(y))
          mfccs = np.mean(librosa.feature.mfcc(y=y, sr=sr, n_mfcc=40).T, axis=0)
          mel = np.mean(librosa.feature.melspectrogram(y, sr=sr).T, axis=0)
          contrast = np.mean(librosa.feature.spectral_contrast(S=stft, sr=sr).T, axis=0)
          tonnetz = np.mean(librosa.feature.tonnetz(y=librosa.effects.harmonic(y), sr=sr).T, axi
          chroma = np.mean(librosa.feature.chroma_stft(S=stft, sr=sr).T,axis=0)
          features = np.hstack([mfccs,chroma,mel,contrast,tonnetz])
          features = features.reshape(1, -1)
In [128]: clf = tree.DecisionTreeClassifier(max_depth=5)
          clf.fit(X, Y_gender)
          pred = clf.predict(features)
          pred
Out[128]: array(['Male'], dtype=object)
In [129]: clf = tree.DecisionTreeClassifier(max_depth=5)
          clf.fit(X, Y_age)
          pred = clf.predict(features)
          pred
```

```
Out[129]: array(['Adult'], dtype=object)
In [130]: clf = tree.DecisionTreeClassifier(max_depth=1)
          clf.fit(X, Y_dialect)
         pred = clf.predict(features)
         pred
Out[130]: array(['American'], dtype=object)
In [149]: from imblearn.over_sampling import RandomOverSampler
         ros = RandomOverSampler()
         X_resampled, y_resampled = ros.fit_sample(X, Y_gender)
         x_re_gender = pd.DataFrame(data=X_resampled, columns=X.columns)
         y_re_gender = pd.DataFrame({"gender": y_resampled})
         hyperparams = [1, 5, 10, 50, 100]
          accuracy = []
          for params in hyperparams:
              clf = tree.DecisionTreeClassifier(max_depth=params)
              scores = cross_val_score(clf, x_re_gender, y_re_gender['gender'], cv=5)
              accuracy.append(scores.mean())
          d = pd.DataFrame({"hyperparams": hyperparams, "accuracy": accuracy})
          d.plot(x="hyperparams", y="accuracy")
Out[149]: <matplotlib.axes._subplots.AxesSubplot at 0x113c56c50>
```

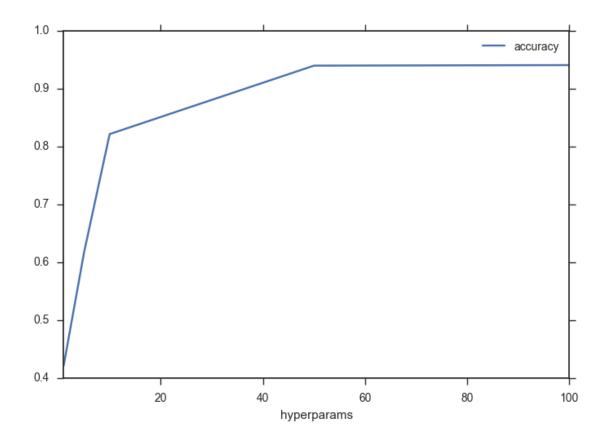


```
In [151]: ros = RandomOverSampler()
    X_resampled, y_resampled = ros.fit_sample(X, Y_age)
    x_re_age = pd.DataFrame(data=X_resampled, columns=X.columns)
    y_re_age = pd.DataFrame({"age": y_resampled})

    hyperparams = [1, 5, 10, 50, 100]
    accuracy = []

for params in hyperparams:
    clf = tree.DecisionTreeClassifier(max_depth=params)
    scores = cross_val_score(clf, x_re_age, y_re_age['age'], cv=5)
    accuracy.append(scores.mean())

d = pd.DataFrame({"hyperparams": hyperparams, "accuracy": accuracy})
    d.plot(x="hyperparams", y="accuracy")
Out [151]: <matplotlib.axes._subplots.AxesSubplot at 0x11642d588>
```

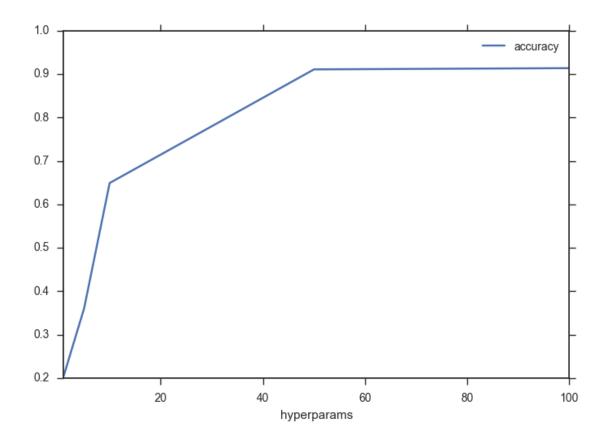


```
In [152]: ros = RandomOverSampler()
    X_resampled, y_resampled = ros.fit_sample(X, Y_dialect)
    x_re_dialect = pd.DataFrame(data=X_resampled, columns=X.columns)
    y_re_dialect = pd.DataFrame({"dialect": y_resampled})

    hyperparams = [1, 5, 10, 50, 100]
    accuracy = []

for params in hyperparams:
    clf = tree.DecisionTreeClassifier(max_depth=params)
    scores = cross_val_score(clf, x_re_dialect, y_re_dialect['dialect'], cv=5)
    accuracy.append(scores.mean())

d = pd.DataFrame({"hyperparams": hyperparams, "accuracy": accuracy})
    d.plot(x="hyperparams", y="accuracy")
Out[152]: <matplotlib.axes._subplots.AxesSubplot at 0x1142fc1d0>
```



## In []:

```
clf_age1.fit(x_re_age, y_re_age['age'])
          clf_age2 = tree.DecisionTreeClassifier(max_depth=30)
          clf_age2.fit(x_re_age, y_re_age['age'])
          clf_age3 = tree.DecisionTreeClassifier(max_depth=20)
          clf_age3.fit(x_re_age, y_re_age['age'])
          clf_age4 = tree.DecisionTreeClassifier(max_depth=10)
          clf_age4.fit(x_re_age, y_re_age['age'])
          clf_dialect = tree.DecisionTreeClassifier(max_depth=50)
          clf_dialect.fit(x_re_dialect, y_re_dialect['dialect'])
          clf_dialect1 = tree.DecisionTreeClassifier(max_depth=40)
          clf_dialect1.fit(x_re_dialect, y_re_dialect['dialect'])
          clf_dialect2 = tree.DecisionTreeClassifier(max_depth=30)
          clf_dialect2.fit(x_re_dialect, y_re_dialect['dialect'])
          clf_dialect3 = tree.DecisionTreeClassifier(max_depth=20)
          clf_dialect3.fit(x_re_dialect, y_re_dialect['dialect'])
          clf_dialect4 = tree.DecisionTreeClassifier(max_depth=10)
          clf_dialect4.fit(x_re_dialect, y_re_dialect['dialect'])
Out[186]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=10,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_split=1e-07, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      presort=False, random_state=None, splitter='best')
In [221]: y, sr = librosa.load("/Users/reyno392/Desktop/Programming/bigdataproject/me.wav", sr=2
          spectrogram = np.abs(librosa.stft(y))
         melspec = librosa.feature.melspectrogram(y=y, sr=sr)
          stft = np.abs(librosa.stft(y))
         mfccs = np.mean(librosa.feature.mfcc(y=y, sr=sr, n_mfcc=40).T, axis=0)
         mel = np.mean(librosa.feature.melspectrogram(y, sr=sr).T, axis=0)
          contrast = np.mean(librosa.feature.spectral_contrast(S=stft, sr=sr).T, axis=0)
          tonnetz = np.mean(librosa.feature.tonnetz(y=librosa.effects.harmonic(y), sr=sr).T, axi
          chroma = np.mean(librosa.feature.chroma_stft(S=stft, sr=sr).T,axis=0)
          features = np.hstack([mfccs,chroma,mel,contrast,tonnetz])
          features = features.reshape(1, -1)
          pred = clf_gender2.predict(features)
          print(pred)
          pred = clf_age2.predict(features)
```

clf\_age1 = tree.DecisionTreeClassifier(max\_depth=40)

```
print(pred)
         pred = clf_dialect2.predict(features)
         print(pred)
['Male']
['Adult']
['American']
In [198]: y_pred_gender = clf_gender1.predict(X)
          y_pred_age = clf_age1.predict(X)
         y_pred_dialect = clf_dialect1.predict(X)
In [199]: from sklearn.metrics import f1_score, precision_score, recall_score, classification_re
          print("gender accuracy score: " + str(accuracy_score(Y_gender, y_pred_gender)))
         print("gender f1_score: " + str(f1_score(Y_gender, y_pred_gender, average="macro")))
          print("gender precision: " + str(precision_score(Y_gender, y_pred_gender, average="mac
         print("gender recall: " + str(recall_score(Y_gender, y_pred_gender, average="macro"))
          print("age accuracy score: " + str(accuracy_score(Y_age, y_pred_age)))
          print("age f1_score: " + str(f1_score(Y_age, y_pred_age, average="macro")))
          print("age precision: " + str(precision_score(Y_age, y_pred_age, average="macro")))
         print("age recall: " + str(recall_score(Y_age, y_pred_age, average="macro")) + "\n")
         print("dialect accuracy score: " + str(accuracy_score(Y_dialect, y_pred_dialect)))
          print("dialect f1_score: " + str(f1_score(Y_dialect, y_pred_dialect, average="macro"))
         print("dialect precision: " + str(precision_score(Y_dialect, y_pred_dialect, average="
          print("dialect recall: " + str(recall_score(Y_dialect, y_pred_dialect, average="macro"
gender accuracy score: 0.999937019776
gender f1_score: 0.999849886751
gender precision: 0.999735589635
gender recall: 0.999964255076
age accuracy score: 0.996913969014
age f1_score: 0.980250719912
age precision: 0.963784183296
age recall: 0.998799813849
dialect accuracy score: 1.0
dialect f1_score: 1.0
dialect precision: 1.0
dialect recall: 1.0
In [203]: print(clf_gender.score(X, Y_gender))
         print(clf_gender1.score(X, Y_gender))
```

```
print(clf_gender2.score(X, Y_gender))
          print(clf_gender3.score(X, Y_gender))
          print(clf_gender4.score(X, Y_gender))
          print()
          print(clf_age.score(X, Y_age))
          print(clf_age1.score(X, Y_age))
          print(clf_age2.score(X, Y_age))
          print(clf_age3.score(X, Y_age))
          print(clf_age4.score(X, Y_age))
          print()
          print(clf_dialect.score(X, Y_dialect))
          print(clf_dialect1.score(X, Y_dialect))
          print(clf_dialect2.score(X, Y_dialect))
          print(clf_dialect3.score(X, Y_dialect))
          print(clf_dialect4.score(X, Y_dialect))
1.0
0.999937019776
0.999244237309
0.99565436453
0.972666582693
0.999937019776
0.996913969014
0.994268799597
0.96888776924
0.763131376748
1.0
1.0
0.997228870135
0.952890792291
0.513477767981
In [159]: clf_age.score(X, Y_age)
Out [159]: 0.99905529663685599
In [160]: clf_dialect.score(X, Y_dialect)
Out[160]: 1.0
In [205]: tree.export_graphviz(clf_gender4, out_file='Desktop/Programming/bigdataproject/tree-ge
          tree.export_graphviz(clf_age3, out_file='Desktop/Programming/bigdataproject/tree-age.d
```

tree.export\_graphviz(clf\_dialect3, out\_file='Desktop/Programming/bigdataproject/tree-d

```
In [217]: from sklearn.externals import joblib
          joblib.dump(clf_gender4, 'Desktop/Programming/bigdataproject/cfl_gender.pkl')
          joblib.dump(clf_age3, 'Desktop/Programming/bigdataproject/cfl_age.pkl')
          joblib.dump(clf_dialect, 'Desktop/Programming/bigdataproject/cfl_dialect.pkl')
Out[217]: ['Desktop/Programming/bigdataproject/cfl_dialect.pkl']
In [234]: from sklearn import neighbors
          clf_kneighbors_gender = neighbors.KNeighborsClassifier(n_neighbors=2)
          clf_kneighbors_gender.fit(x_re_gender, y_re_gender['gender'])
          clf_kneighbors_age = neighbors.KNeighborsClassifier(n_neighbors=3)
          clf_kneighbors_age.fit(x_re_age, y_re_age['age'])
          clf_kneighbors_dialect = neighbors.KNeighborsClassifier(n_neighbors=7)
          clf_kneighbors_dialect.fit(x_re_dialect, y_re_dialect['dialect'])
Out[234]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=1, n_neighbors=7, p=2,
                     weights='uniform')
In [235]: print(clf_kneighbors_gender.score(X, Y_gender))
          print(clf_kneighbors_age.score(X, Y_age))
          print(clf_kneighbors_dialect.score(X, Y_dialect))
0.993387076458
0.9820506361
0.895137926691
In [238]: y, sr = librosa.load("/Users/reyno392/Desktop/Programming/bigdataproject/derp.wav", sr
          spectrogram = np.abs(librosa.stft(y))
          melspec = librosa.feature.melspectrogram(y=y, sr=sr)
          stft = np.abs(librosa.stft(y))
         mfccs = np.mean(librosa.feature.mfcc(y=y, sr=sr, n_mfcc=40).T, axis=0)
         mel = np.mean(librosa.feature.melspectrogram(y, sr=sr).T, axis=0)
          contrast = np.mean(librosa.feature.spectral_contrast(S=stft, sr=sr).T, axis=0)
          tonnetz = np.mean(librosa.feature.tonnetz(y=librosa.effects.harmonic(y), sr=sr).T, axi
          chroma = np.mean(librosa.feature.chroma_stft(S=stft, sr=sr).T,axis=0)
          features = np.hstack([mfccs,chroma,mel,contrast,tonnetz])
          features = features.reshape(1, -1)
          pred = clf_kneighbors_gender.predict(features)
         print(pred)
         pred = clf_kneighbors_age.predict(features)
         print(pred)
          pred = clf_kneighbors_dialect.predict(features)
          print(pred)
```

```
['Male']
['Adult']
['Canadian']

In []:

In []:

In []:
```

In []: